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Factory Eco-Efficiency Modelling: Framework Development and Testing

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Abstract: Eco-efficiency is becoming an increasingly important organisational performance measure. Its indicators are regularly used alongside productivity, cost, quality, health and safety in operations and corporate social responsibility reporting. The purpose of this paper is to show an eco-efficiency modelling framework, and its application in the case of an automotive manufacturer. The framework composes, models and analyses resource and production data. Focus on energy, water distributions and material transformations in manufacturing, utility and facility assets are used to analyse eco-efficiency. Resources are examined in respect to three data granularity factors: subdivision, pulse, and magnitude. Models are linked with performance indicators to assess asset eco-efficiency. This work contributes to industrial sustainability literature by introducing a modelling framework that links with data granularity and eco-efficiency indicators.

1. Introduction

Formalised in the WBCSD's 1992 Changing Course publication, eco-efficiency is proposed as the main strategy for promoting sustainability, by living within global resource carrying capacity [1]. Although eco-efficiency is a well-established concept, it is only beginning to be embraced by the wider business community. Promoted by legislative policies and standards such as ISO140001, resource improvement of factories is becoming an essential objective for manufacturers.

Eco-efficiency is synonymous with management philosophies geared towards factory productivity and resource improvements. Typologies typically focus on environmental and economic indicators [2]. The EEA interpretation used by many manufacturers, defines eco-efficiency as a strategy enabling sufficient delinking of environmental from economic activity (Figure 1). Thus providing equitable access to natural resources for current and future generations [3].

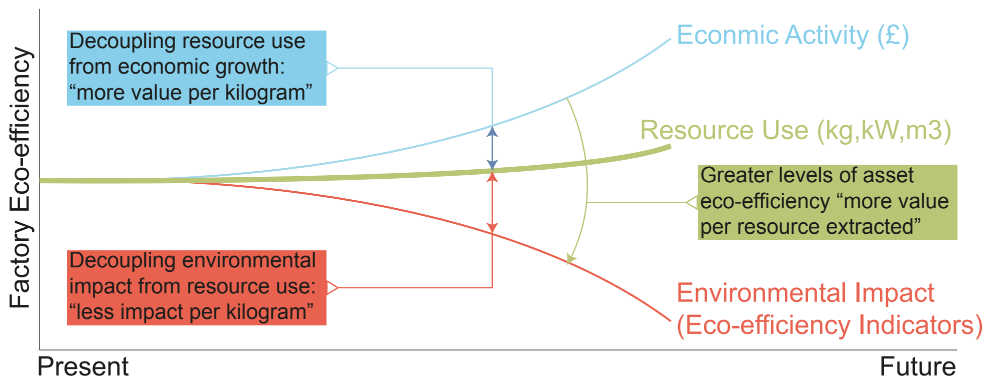

Figure 1: Decoupling environment & economics, yielding eco-efficient resource use

There is a major difference between the EEA and WBCSD definitions. The EEA definition is concerned with comparable relativity, not global carrying capacity. This means that factory systems are audited against themselves and benchmarks. Additionally, neither definition provides a normative standard for resource management [4]. Meaning it is not possible for eco-efficiency frameworks to say which production method is absolutely effective for the environment and economy. Only whether a particular configuration improves or diminishes eco-efficiency, relative to a specified scope.

Moves toward improving factory eco-efficiency are being driven by reductions in resource use [5]. Early interventions seek to reduce energy and materials used in localised areas, such as manufacturing cells [6]. However, there is paucity on impact of combining manufacturing, utility and facility models. In particular there is little consideration for relationship between model assets, data granularity and eco-efficiency performance indicators. Data granularity refers to the extent of which a factory's data can be isolated into distinguishable pieces. Therefore, subdividing resource pulse and magnitude data by linking to factory technical assets is logical.

This paper uses literature as a basis for developing a factory eco-efficiency modelling framework based upon data-granularity factors. It is then applied to a UK automotive manufacturer's resource and production data to model the eco-efficiency of their paint shop assets. Conclusions on its applicability are provided.

3. Framework Development

As progress is made in eco-efficiency advances become more challenging [7]. To accommodate further resource reduction opportunities an expansion of scope (Figure 2), integrating resources across functional boundaries of manufacturing, utilities and facilities assets is necessary [8].

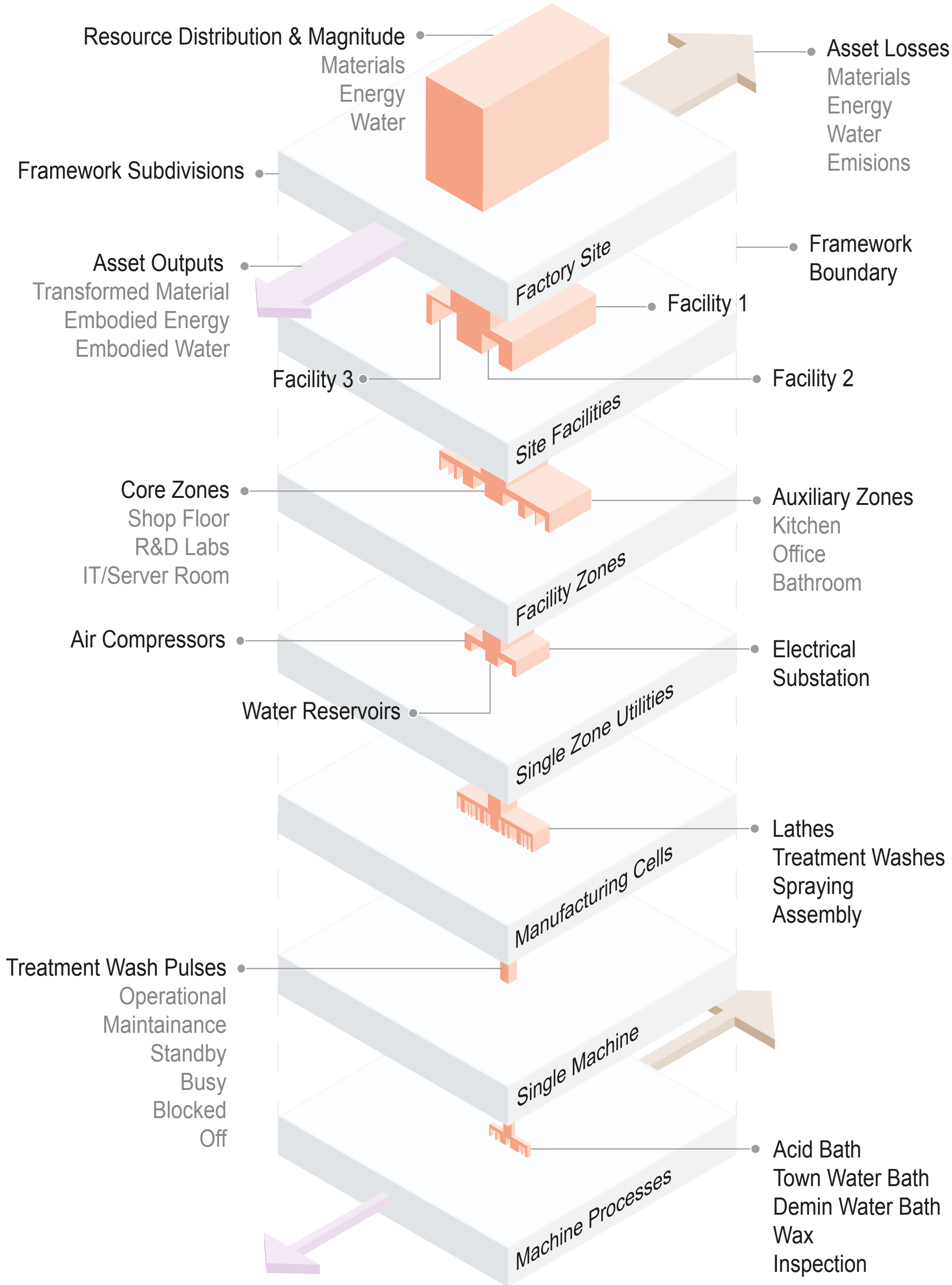

Figure 2:Framework schema integrates resource subdivision, pulse and magnitude
*Specified assets/resources are non-exhaustive and for demonstration purposes only

A structured approach has been used to review eco-efficiency and modelling literature to derive data granularity factors, and functional elements of the factory eco-efficiency modelling framework.

3.1 Factory Asset Subdivisions

Examining factories as an integration of manufacturing, utilities and facilities is necessary to consider the distribution of resources, and how these relate to technical assets within a factory site [9]. This scale of analysis brings with it the complexity of composing a variety of discrete data pulses and magnitudes across asset subdivisions [10]. For example a facility may have a combination of manufacturing cells, sourcing different energies from utilities, which additionally supply other core and auxiliary zones. Therefore the framework must correlate subdivisions with other data granularity factors, whilst linking with relevant eco-efficiency indicators. Data composition is a crucial pre-requisite for building representative asset models, which turns often-disparate raw data into information on asset eco-efficiency performance. Presently, there is paucity in eco-efficiency and modelling literature for data composition and asset modelling with appropriate indicators using data granularity factors.

The need to be more eco-efficient provides the momentum organisations require for pursuing factory modelling [11]. However, beyond Lean there is little to support the analysis of resource-use across asset subdivisions [12]. Current modelling tools and techniques are informed by detailed knowledge of narrow functional boundaries [13]. Making applicability limited by their bespoke relationship with pre-defined assets, and a lack of knowledge beyond point-solutions for how individual asset configurations integrate within their wider system.

A means for understanding factory eco-efficiency through data granularity factors, including the subdivision of technical assets, is required. The framework aims to develop knowledge in this area through data composition within and across subdivisions, by linking assets with relevant performance indicators. Framework models can be assembled at selected subdivisions appropriate to organisations eco-efficiency objectives. It has been designed to satisfy versatile user requirements, essential in developing representational factory models, with the ability to measure asset eco-efficiency [14].

3.2 Eco-efficiency Performance Indicators and Resource magnitudes

There are recognised approaches that address eco-efficiency indicators and the magnitude of resource impacts conceptually. Examples include Industrial Ecology, Reduce, Reuse and Recycle and Green-Supply Chain Management. However, quantifying eco-efficiency for energy and material resources flowing through a factory system is difficult to evaluate using conceptual approaches alone. Despite widespread dissemination of existing eco-efficiency improvement initiatives, and reported studies exemplifying economic [15] and environmental [16] benefits, implementation barriers continue [17]. Examination of the literature suggests a lack of systematic rigour and repeatability in the application and scalability of performance indicators for modelling resource magnitudes.

Contrary to eco-efficiency literature, operations management provides established improvement methods for process optimisation. Methods include six sigma, DMAIC and value stream mapping, which detail behaviours for standardising productivity improvement efforts. Indicators in this area focus on production inventory, quality and cycle time [18]. Operations management is widely used in industry. However, performance improvement is on productivity, of which improvements in resource magnitudes are a beneficial side effect. Material flow analysis and life cycle assessment of resource magnitude exist. Although structured by performance indicators for eco-efficiency, which are beneficial from a CSR perspective [19], their models have a limited ability to capture resource distribution dynamically. Making their applicability questionable at some subdivisions such as those of manufacturing cells, single machine and machine processes. These subdivisions require dynamic models with per-minute to per-second pulses of resource magnitudes to provide improvement opportunities.

The framework performance indicators include: power factor, water footprint, energy mix, material yield, energy per unit and thermodynamic minimums. Many performance indicators are applicable at multiple subdivisions. However some such as thermodynamics minimum and energy per unit are more applicable at manufacturing cells and single machine subdivisions. Whereas energy mix and power factor are more applicable at facilities and facility zones, when a number of assets are required to be eco-efficient. Framework performance indicators are linked with resources magnitudes across asset subdivisions. Facility assets (e.g. air conditioning) operate in relation to manufacturing asset requirements (e.g. paint shop temperature and humidity). Utility assets may also share resources with building and manufacturing assets (e.g. hot/cold water circuits, steam pumps etc.). Therefore, attention in the framework is given to relationship and scale resource magnitudes across subdivisions. Once data granularities are accurately composed, they are coupled with performance indicators in the modelling environment.

3.3 Modelling and Pulses

Modelling is widely used within facilities [20], utilities [21] and manufacturing [22] design and operations. Generally assets for each domain are modelled and improved independently. This restriction in scope can be caused by the disparities in pulses between selected assets. Leading to complications in the control of a factory system [23] and increasing the potential of sub-optimal results [24].

Additionally, there are an ever-increasing number of modelling tools [50] being used within these domains. Making selection of an appropriate eco-efficiency method and tool more complicated [25].

Facility assets are modelled within tools like IES<VE>, MicroStation and Ecotect. These tools focus on the eco-efficiency of assets during the design and construction phases (e.g. embodied carbon) of a facility's lifecycle, and not on the performance of facility assets throughout operations. Therefore, pulses for these assets have a relatively coarse granularity specific for designing and constructing building fabric eco-efficiently. Manufacturing modelling tools on the other hand, focus on operational eco-efficiency. Discrete-event simulation tools for production include Witness, Arena and Simul8. These are normally use finer pulse granularities to assess asset details such as processing costs, cycle-times and queue buffering. This distinction in pulse granularity is important for linking between subdivisions. Additionally, these modelling tools are able to simulate both continuous flows and discrete events, making them useful for modelling continuous resources (e.g. water) alongside discrete manufacturing (e.g. machining), utility (e.g. pump) and facility (e.g. lighting) assets.

Modelling is a recognised tool for providing the necessary dynamic environment to measure eco-efficiency within different ranges of pulses. However, more guidance on the applicability of specific pulse granularities to accurately compose, model and indicate eco-efficiency is still required. The framework contributes to this area by consolidating subdivisions with resource data at given pulses. Quantifying eco-efficiency through models to produce a comprehensive understanding of the factory system, in which the modelled assets operate [26].

To develop knowledge in the area of data granularity the factory eco-efficiency modelling framework uses a structured data composition and modelling approach. This helps modellers move beyond current-tendencies of developing localised point-solutions. Framework modelling results can be used to measure and determine improvement opportunities at single or multiple data granularities, based on the application of best practices from specific industries [27]. Framework models incorporate the evaluation of energy distributions and material transformations within technical assets [28]. Allowing eco-efficiency indicators, to systematically measure and improve factory performance [29].

3.4 Factory Eco-efficiency Modelling Framework

This framework is used to measure resources consumed by assets and improve operational eco-efficiency within the factory site. Each subdivision of the framework considers assets at greater detail through progressively modelling finer data granularities. Modelling focuses on the dynamic behaviour of system inputs, outputs, controllers and losses (figure 3) to show asset subdivision eco-efficiency based upon pulse frequency and resource magnitudes.

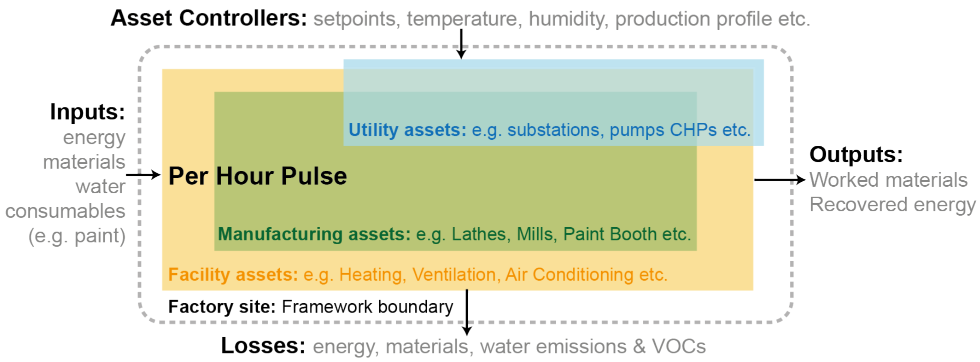

Figure 3: Conceptual model designed to work with framework data granularities

The framework integrates resource, production and cost data sets, which are measured in modelling environments. A process flowchart (figure 4) shows the modelling method applied in the case. The case application shows how facility zones, single zone utilities and manufacturing cells subdivisions are used to analyse eco-efficiency performance of associated assets.

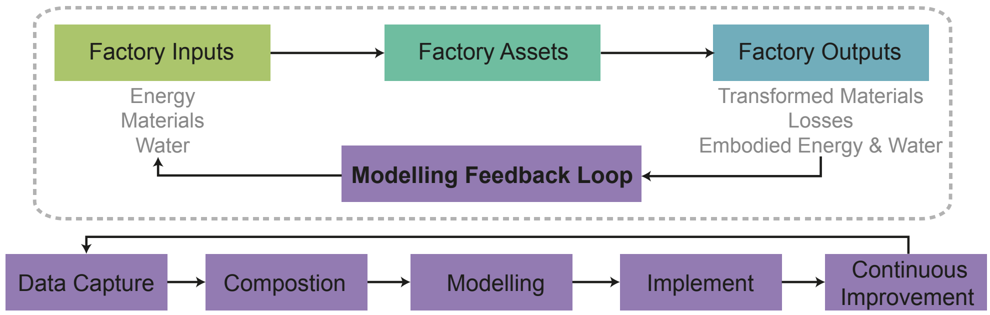

Figure 4: Modelling process flowchart shows how the framework can be applied

4. Modelling Case Application

Indisputably, the highest resource consuming facility in automotive manufacturing is the paint plant, accounting for 45%–70% of total energy used in production [30]. In the case of this automotive manufacturer, the paint plant is operated 6.5 days per week, with asset maintenance occurring over the remaining 0.5 days. Three types of aluminium (Al) and steel (Fe) vehicle bodies are washed, dried, sprayed, polished, waxed and inspected, prior to dispatch. Water, gas, and electricity resources are distributed through utility assets for use in manufacturing.

Ecopare ltd. has captured detailed per-hour data for resource distributions within paint plant assets from 10-16th November 2014. The captured data has been composed using Facility Zones, Utilities (SGL zone) and manufacturing cells subdivisions (Table 1). Sense checks and unit conversions were completed to allow meaningful analysis, using a simplified flow scheme model, and resource distribution profile for the highlighted treatment line assets to visualise energy/water per unit, and energy mix eco-efficiency performance.

Facility Zones	Single Zone Utilities	Manufacturing Cells	Pulse	Magnitude
Paint Plant - Zone 3	Town Water	Skid Wash	09:00	121.68 kL
Paint Plant - Zone 3	Town Water	Skid Wash	10:00	238.68 kL
Paint Plant - Zone 4	Demin Water	Treatment Lines	09:00	1100.56 kL
Paint Plant - Zone 4	Demin Water	Treatment Lines	10:00	1240.02 kL

Table 1: Composed data shows asset subdivisions with intervals and magnitudes

Facility zones data shows that the cumulative total for mean water distribution across assets is 880kL over the operating week. Additionally, electrical assets consume a mean of 33,864kW over the operating week. For brevity, the model (Figure 5) shows water distribution and material transformations occurring per hour. This model quantifies the water-footprint of paint plant assets, identifying the largest resource consumer for further analysis within a resource distribution profile.

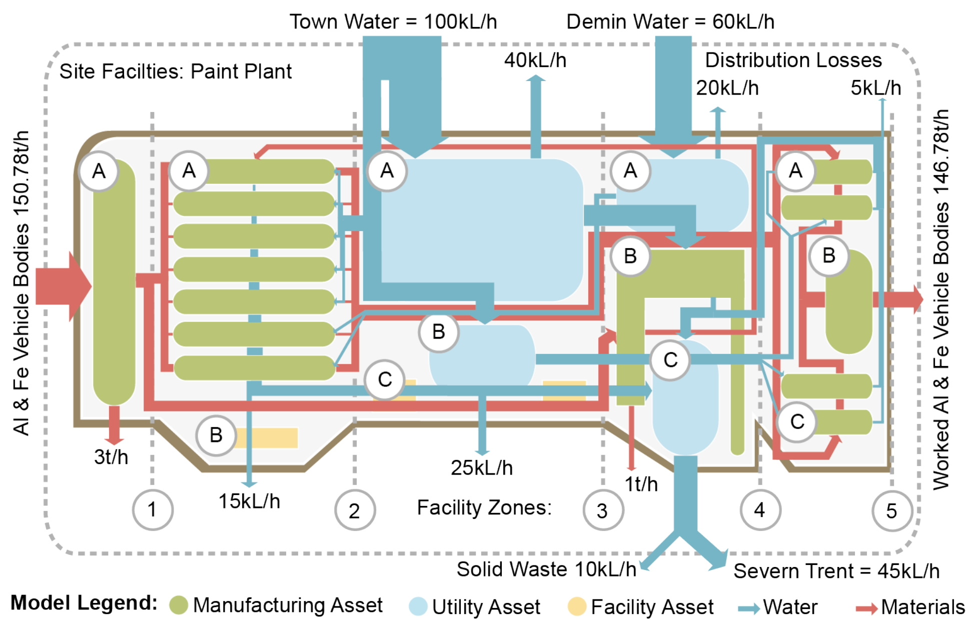

Figure 5: Model quantifies material transformations and water distribution per hour

5. Modelling Results and Analysis

Model results (figure 6) show the relationship between material transformations and water use, across paint plant assets. The model visualises subdivision and magnitude data on resource inputs, controllers, outputs and losses.

Mean Water Footprint (kl/h):

1 A Pre-treat inspect = 0.00		
2 A Treatment Lines = 983.39	B AHU1 = 12.63	
3 A Central Reservoir = 650.00	B TCB Reservoir = 554.89	C AHU2 (x2) = 35.52
4 A Demin Reservoir = 420.00	B Skid Wash = 223.46	C Effluent Reservoir = 180.00
5 A Top Coat Booths = 26.31	B Post-treat inspect = 0.00	C Wax Booths =9.87

Figure 6: Modelling of assets mean water footprint to indicate large consumers

The largest average consumption of town and demineralised water (983.39kL/h) occurs in the Treatment Line manufacturing cell. Therefore, a distribution profile for all resources was undertaken (Figure 7) to show pulses and calculate energy per unit, water per unit and energy mix eco-efficiency indicators (Table 2).

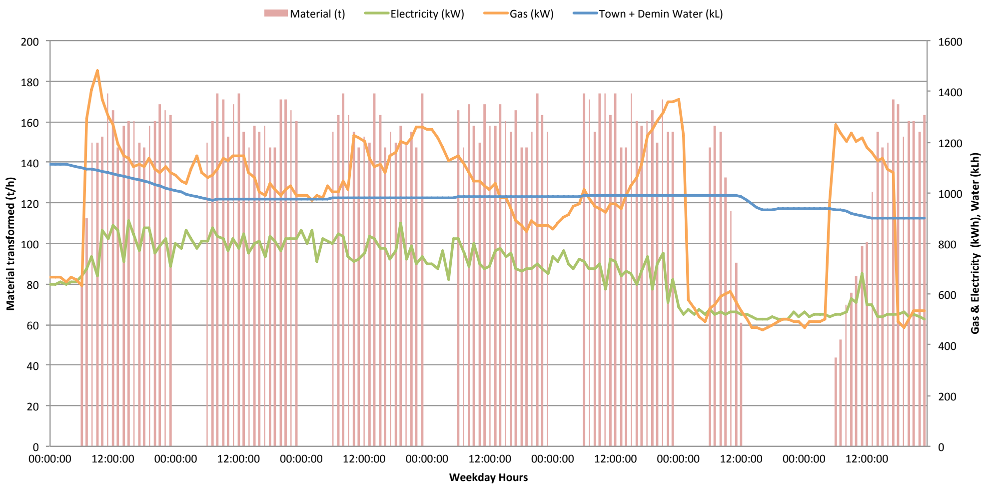

Figure 7: Treatment Line manufacturing cell resource distribution profile

Indicator	Metrics	Result
Energy per Unit 1	kW(Gas+Elec)/kg(2570)	41.77
Energy per Unit 2	kW(Gas+Elec)/kg(2398)	38.98
Energy per Unit 3	kW(Gas+Elec)/kg(3050)	49.58
Water per Unit 1	kL/kg(2570)	31.49
Water per Unit 2	kL/kg(2398)	29.37
Water per Unit 3	kL/kg(3050)	37.36
Energy Mix per hr*	Non-renewable to renewable ratio	5.67:1

*15% of all energy delivered is derived from renewable sources.

Table 2: Eco-efficiency calculations for treatment line manufacturing cell resources

Information from the simplified flow scheme and resource distribution profile is highlighted within the eco-efficiency indicators. Application of the framework demonstrates modelling at progressive levels of detail, based upon data granularity subdivision, pulse and magnitude factors. These results structure the treatment line asset resource-use baseline. Recommendations such as changing asset set points, re-aligning resource with production profiles, and synchronising assets to allow for resource cascading, can be made to increase eco-efficiency. Prior to implementation, the framework can be used to build simulation models to test any potential technical interventions. Assessing the level of eco-efficiency improvement with various model configurations.

5. Framework Applicability and Case Conclusions

The framework has been designed to further factory eco-efficiency modelling knowledge using data granularity. It combines assets with resources, and eco-efficiency indicators within quantitative models. The reason for undertaking this work comes from the realisation that the quality of technical interventions in factories is governed by the accuracy of data granularity, the types of models developed and particular eco-efficiency indicators applied in analysis.

This paper has shown that the framework is useful for developing models, which visualise asset eco-efficiency performance. In this case the framework is used to understand the data granularity of resources within a paint plant. Resource and production data across facility zone, utilities and manufacturing cell subdivisions, with per hour pulses and magnitudes are composed and modelled to determine the eco-efficiency baseline for the treatment line manufacturing cell. It contributes new knowledge to the area of industrial sustainability by showing how data granularity can be used to compose, model and indicate asset eco-efficiency.

Future work will focus on the development of simulating asset configurations to measure eco-efficiency as basis for providing implementable technical interventions.

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